ANALSING THE EFFECT OF COMMUNICATION, ENERGY, AND TRANSPORT INFRASTRUCTURE INVESTMENT ON FOREIGN DIRECT INVESTMENT IN SELECTED SOUTHERN AFRICA DEVELOPMENT COMMUNITY (SADC) COUNTRIES – A PANEL DATA APPROACH

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ABSTRACT

Infrastructure investment is a key driver of economic growth, especially in developing regions like the Southern Africa Development Community (SADC). This study evaluates the effect of communication, energy, and transport infrastructure investments on Foreign Direct Investment (FDI) inflows in South Africa, Seychelles, Madagascar, and Mauritius from 1990 to 2022. Using a panel data approach, the research explores the relationship between infrastructure investments and FDI, guided by the Resource-Based View (RBV) and New Economic Geography theories. These frameworks emphasize how improved infrastructure reduces operational costs, enhances economic competitiveness, and attracts foreign investment, offering valuable insights for fostering sustainable development.

The study employs robust econometric methods, including the Panel Autoregressive Distributed Lag (PARDL) and Panel Correlated Standard Error (PCSE) models, to analyse short- and long-term effects. Results show that transport and energy infrastructure investments significantly boost FDI inflows in the long term, while the influence of communication infrastructure appears statistically insignificant. The Dumitrescu-Hurlin panel causality test identifies unidirectional causality from energy and communication infrastructure to FDI, emphasizing their importance in attracting foreign investments. Unit root and cointegration tests confirm a long-run equilibrium relationship among the variables, indicating that infrastructure investments and FDI inflows move together over time. These findings highlight the need for targeted investments in transport and energy infrastructure to enhance the regions attractiveness to foreign investors. This study contributes to the literature by providing empirical evidence from the SADC context, offering actionable recommendations for policymakers to optimize FDI inflows and drive economic growth.

Keywords: Infrastructure Investment, SADC, PARDL, PCSE, Foreign Direct Investment, Transport, Energy, Communication

1. INTRODUCTION

Foreign Direct Investment (FDI) is a critical catalyst for economic growth, particularly in developing regions like the Southern Africa Development Community (SADC). While developed nations utilize FDI to sustain long-term growth, emerging economies rely on it to drive development and bridge infrastructure gaps (UNCTAD, 2023). Infrastructure services—such as energy, transport, and communication—are indispensable for improving productivity, expanding markets, and supporting economic activities (Asiedu, 2022). However, many developing countries, including those in the SADC, struggle to unlock the full potential of infrastructure investments. For instance, Sub-Saharan Africa faces an annual infrastructure funding gap of approximately $46 billion, which severely hampers economic progress (Calderón & Servén, 2021).

Despite incremental advancements, infrastructure deficits continue to pose significant challenges in the SADC region. Limited electricity access, underdeveloped transport networks, and unreliable power supplies

undermine FDI inflows, increase operational costs, and reduce regional competitiveness (African Development Bank, 2022). These challenges are particularly evident in Madagascar, where poor infrastructure inflates costs by 40%, and in South Africa, where energy crises have led to a 20% decline in FDI inflows (Mendes et al., 2023; World Bank, 2023). This paper addresses critical gaps in the literature by examining how communication, energy, and transport infrastructure investments influence FDI inflows in SADC countries, particularly South Africa, Seychelles, Madagascar, and Mauritius, from 1990 to 2022. By adopting a regional approach and employing advanced econometric techniques, this study aims to provide insights into infrastructure-FDI dynamics, offering practical guidance for policymakers to optimize FDI inflows and foster sustainable economic development.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, Section 3 outlines the methodology, Section 4 presents the results and discussion, and Section 5 concludes with policy recommendations.

2. LITERATURE REVIEW

This paper used the Resource-Based View (RBV) and the New Economic Geography Theory to explain the relationship between foreign direct investment (FDI) and infrastructure investment in communication, transport, and energy sectors. The RBV, developed by researchers such as Barney (1991) and Wernerfelt (1984), highlights the strategic importance of unique internal resources for attaining a sustainable competitive advantage. It posits that a well-developed infrastructure network serves as a valuable resource for nations, enhancing their attractiveness to foreign investors through improved productivity, reduced costs, and enhanced economic efficiency. Despite its focus on internal resources, critiques from researchers like Porter (1985) argue that RBV underestimates the role of external market dynamics in shaping competitiveness. Nonetheless, RBV remains relevant by emphasizing infrastructure as a critical resource for economic development and competitiveness, thereby underscoring the importance of strategic investments in transport, communication, and energy infrastructure to attract FDI.

The New Economic Geography Theory emphasizes the spatial distribution of economic activities influenced by infrastructure development (Santos-Paulino, Squicciarini & Fan, 2014). This theory highlights how investments in transportation infrastructure reduce geographical barriers and promote agglomeration effects, attracting FDI to regions with improved connectivity. Research by Redding and Venables (2004) and Baldwin and Forslid (2006) supports this view, demonstrating that better infrastructure connectivity enhances accessibility and lowers trade costs, which aligns with the study's focus on infrastructures impact on FDI inflows in SADC countries.

Empirical literature supports the theoretical perspectives by examining the linkages between FDI and various infrastructure investments. On communication infrastructure, Asiedu (2021) and Bhorat (2019) found that improved communication networks foster innovation, expand markets, and boost business efficiency, thereby attracting FDI inflows. Asiedu employed a panel ARDL model, while Bhorat used VECM analysis, both highlighting the economic benefits of mobile communication services and their pivotal role in drawing foreign investments. Similarly, Bonga-Bonga (2021), using GMM estimation, emphasized telecommunications infrastructures contribution to connectivity and market access, facilitating smoother business operations. Osei-Assibey (2020) corroborated these findings through a VECM analysis, affirming the importance of robust ICT infrastructure in enhancing operational efficiency and attracting FDI. Collectively, these studies underscore the critical role of communication infrastructure in fostering economic growth and investment attractiveness in the SADC region.

On transport infrastructure, Santos Silva (2018) and Mlachila (2022) emphasized its importance in reducing trade costs and enhancing market access, with both studies employing cointegration and ARDL

approaches, respectively. Naude (2019) and Vani (2021) extended these arguments using GMM and DOLS estimators, demonstrating how well-developed road networks lower operational costs and improve supply chain efficiency, attracting higher levels of FDI. These findings highlight transport infrastructure as a foundational driver of economic development and FDI inflows.

Energy infrastructure has also been identified as a critical determinant of FDI attraction. Munnell (2017) highlighted the importance of reliable and affordable energy supply for economic development through a panel ARDL approach. Briceño- Garmendia (2020), using fixed-effects models, and Lim (2018), employing a VECM approach, both emphasized the positive relationship between energy infrastructure investment and FDI inflows. Xu (2022) further explored renewable energy projects, using GMM estimation to show their dual role in promoting environmental sustainability and enhancing FDI attractiveness. These studies collectively highlight the evolving role of energy infrastructure in shaping FDI patterns, with a clear shift toward sustainable development initiatives.

Finally, the causal relationships between infrastructure investment and FDI have been explored using various econometric techniques. Afolayan et al. (2022) identified bidirectional causality between transport infrastructure and FDI, suggesting that infrastructure improvements attract FDI, which in turn stimulates further investments. Adeniran and Johnson (2023) found unidirectional causality from energy infrastructure to FDI, emphasizing the role of stable energy supply in investment decisions. Bwalya and Phiri (2023) highlighted the causal link between communication infrastructure and FDI inflows, demonstrating how enhanced connectivity reduces transaction costs and improves business efficiency. These findings underline the interdependence between infrastructure development and FDI, illustrating a mutually reinforcing relationship that drives economic growth in SADC countries.

3. RESEARCH METHODOLOGY

3.1 Data and Model specification

This study utilized data freely obtained from the World Bank, covering the period from 1990 to 2022 for selected SADC countries, including South Africa, Seychelles, Madagascar, and Mauritius. The dependent variable was FDI inflows, while the independent variables were energy infrastructure (proxied by access to electricity (% of population)), communication infrastructure (proxied by ICT service exports (BoP, current US$)), and transport infrastructure (proxied by air transport, passengers carried).

The model specification aimed to investigate the effect of infrastructure investment on FDI using the following regression model:

$$FDI_{it} = \beta_{0it} + \beta_1 ENG_{it} + \beta_2 COM_{it} + \beta_3 TRA_{it} + \varepsilon_{it} \text{.....(1)}$$

Where FDI_{it} represents foreign direct investment inflows, ENG_{it} denotes energy infrastructure COM_{it}, indicates communication infrastructure, and TRA_{it} signifies transport infrastructure for country i in year t. To standardize the coefficients, variables such as foreign direct investment, communication infrastructure, and transport infrastructure were transformed into logarithmic form, yielding the following modified equation:

$$LEFI_{it} = \beta_{0it} + \beta_1 ENG_{it} + \beta_2 LCOM_{it} + \beta_3 LTRA_{it} + \varepsilon_{it} \text{.....(2)}$$

Here, $LEFI_{it}$, $LCOM_{it}$, and $LTRA_{it}$ represent the logarithmic transformations, while ε_{it} captures the error term.

3.2 Estimation Techniques

Estimation techniques are pivotal in econometric analysis as they help explore relationships among variables while addressing issues like cross-sectional dependency, heterogeneity, and stationarity, ensuring robust results. Descriptive statistics provide insights into data patterns, while tests for cross-sectional dependency, such as those by Pesaran (2004), assess interdependencies among SADC countries. Homogeneity and heterogeneity tests, like Pesaran and Yamagatas (2008), determine whether effects are uniform or vary across the panel. Stationarity is examined using LLC, IPS, Fisher-ADF, Fisher-PP, and Pesaran-CIPS tests, which ensure variables maintain consistent statistical properties over time. Cointegration tests, including Pedroni, Kao, and Johansen-Fisher, identify long-run equilibrium relationships among non-stationary variables. The Panel Auto-Regressive Distributed Lag (PARDL) model analyses both short- and long-term dynamics, while Panel Correlated Standard Error (PCSE) techniques correct for cross-sectional dependence, ensuring accurate standard errors (Beck & Katz, 1995). Diagnostic tests, like Jarque- Bera, validate residual normality, and stability is verified using the Inverse Roots of AR Characteristic Polynomial. Lastly, the Dumitrescu-Hurlin Panel Causality test examines directional relationships between variables, accounting for panel heterogeneity. These methods collectively ensure reliable and nuanced insights into the impact of infrastructure investment on FDI inflows in SADC countries.

4. EMPIRICAL RESULTS AND DISCUSSIONS

This section presents and discusses the empirical results of the study, focusing on the analysis and interpretation of data using the methods outlined in Section 3. It aims to provide insights into the impact of infrastructure investments on Foreign Direct Investment (FDI) in the selected SADC countries.

4.1 Descriptive statistics results

Table 1. Descriptive statistics test Results

	LFDI	ENG	LCOM	LTRA
Mean	8.309313	51.50186	7.381681	5.971004
Median	8.407571	37.50000	7.098024	5.733430
Maximum	10.60915	100.0000	8.974751	7.418488
Minimum	6.526083	7.800000	5.589299	5.039261
Std. Dev.	0.880835	35.81833	0.783618	0.636318
Skewness	0.142999	0.128420	0.371110	1.014313
Kurtosis	2.262267	1.246578	2.235150	2.595961
Jarque-Bera	3.443252	17.27251	6.247375	23.53215
Probability	0.178775	0.000178	0.043995	0.000008
Sum	1096.829	6798.246	974.3819	788.1725
Sum Sq. Dev.	101.6390	168066.8	80.44147	53.04193
Observations	132	132	132	132

Source: Authors estimations using Eviews 13

The descriptive statistics in Table 1 summarise key features of the variables LFDI, ENG, LCOM, and LTRA, providing insights into their behaviour across 132 observations. The mean values indicate average levels, with LFDI and ENG showing higher averages (8.31 and 51.50, respectively) compared to LCOM and LTRA. The standard deviations reveal that ENG has the highest variability (35.82), while LTRA is the least

variable (0.64). Skewness values indicate moderate symmetry, except for LTRA, which has a noticeable positive skew (1.01). Kurtosis suggests that all variables approximate a normal distribution, though ENG's low kurtosis (1.25) points to fewer extreme values. The Jarque-Bera test results show ENG and LTRA significantly deviate from normality (p-values < 0.05), while LFDI and LCOM are closer to normal distribution thresholds. These statistics highlight the need to address variability and non-normality in further analyses.

4.2 Cross-Sectional Dependency Test Results

The cross-sectional dependency test assesses whether cross-sectional units in a panel are correlated.

Table 2. Cross-Sectional Dependency Test Results

Tests	Stat.	D.F.	Probability value
"Breusch-Pagan LM"	39.03447	6	0.0000
"Pesaran scaled LM"	9.536231		0.0000
"Pesaran CD"	4.117256		0.0000

Source: Authors estimations using Eviews 13

Results in Table 2, derived from Breusch-Pagan LM, Pesaran scaled LM, and Pesaran CD tests, all show p-values of 0.0000, rejecting the null hypothesis of no cross- sectional dependence. This indicates significant interdependence among the countries analysed, due to shared economic conditions or external shocks (Bayoumi & Swiston, 2009). Such dependencies necessitate econometric methods that address cross-sectional dependence, as standard techniques may produce biased results (Pesaran, 2004). The presence of dependency justifies using the Im-Pesaran-CIPS panel unit root test for further analysis (Zhanje & Jeke, 2022).

4.3 Homogeneity/Heterogeniety Test Results

The homogeneity test examines whether the slope coefficients are consistent across cross-sections in the panel model. Table 3 provides the homogeneity (delta) test results for the model, where LFDI is regressed on LCOM, ENG, and LTRA.

Table 3. The homogeneity (delta) test model results

	Statistic	P-Value
Delta_tilde	1.779	0.075
Delta_tilde_adj	1.931	0.053

Source: Authors estimations using Stata 14

The Table 3 results demonstrate that the null hypothesis that the slope coefficients are homogeneous is not rejected at 5% level of significance. This implies that the 2nd generation panel unit root tests should not be included from the homogeneity rest perspective but is justified from the results found in Table 2 of cross dependence test point of view, it indicates that the 2nd generation panel unit root tests must be included, and it will be presented in Table 4.

4.4 Panel Stationarity/Unit Root Test Results

This section evaluates the stationarity properties of the panel data variables using formal unit root tests. Table 4 presents the results from the Levin, Lin & Chu (LLC), Im, Pesaran & Shin (IPS), ADF-Fisher Chi-square, PP-Fisher Chi-square tests, and the second-generation Pesaran-CIPS test. These tests provide critical insights into whether the variables are stationary at levels or require differencing. The inclusion of the Pesaran-CIPS test specifically addresses cross-sectional dependency, ensuring the robustness and reliability of the econometric analysis.

Table 4. Formal panel unit root tests summary results

	Levels		**1st Difference**		
LLC	**Individual intercept**	**Individual intercept + Individual intercept**	**Individual intercept**	**Individual intercept +**	**Conclusion**

		trend		**trend**	
$LFDI_t$	0.0809***	0.2500	_	0.0000*	I(0) Stationary
$LCOM_t$	0.0009*	0.1509	_	0.0000*	I(0) Stationary
ENG_t	0.0490**	0.5285	_	0.0000*	I(0) Stationary
$LTRA_t$	0.5943	0.7148	0.0000*	0.0000*	I(1) Stationary
IPS	**Individual intercept**	**Individual intercept+ trend**	**Individual intercept**	**Individual intercept + trend**	**Conclusion**
$LFDI_t$	0.3538	0.1775	0.0000*	0.0000*	I(1) Stationary
$LCOM_t$	0.3308	0.5387	0.0000*	0.0000*	I(1) Stationary
ENG_t	0.8354	0.9236	0.0000*	0.0000*	I(1) Stationary
$LTRA_t$	0.2369	0.8930	0.0000*	0.0000*	I(1) Stationary
Fisher-ADF	**Individual intercept**	**Individual intercept + trend**	**Individual intercept**	**Individual intercept + trend**	**Conclusion**
$LFDI_t$	0.5453	0.2470	0.0000*	0.0000*	I(1) Stationary
$LCOM_t$	0.1678	0.6323	0.0000*	0.0000*	I(1) Stationary
ENG_t	0.3326	0.9761	0.0000*	0.0000*	I(1) Stationary
$LTRA_t$	0.4007	0.9492	0.0000*	0.0000*	I(1) Stationary
Fisher-PP	**Individual intercept**	**Individual intercept + trend**	**Individual intercept**	**Individual intercept + trend**	**Conclusion**
$LFDI_t$	0.3791	0.0291**	0.0000*	_	I(1) Stationary
$LCOM_t$	0.0004*	0.0905***	_	_	I(0) Stationary
ENG_t	0.0308**	0.1958	_	0.0000*	I(0) Stationary
$LTRA_t$	0.7256	0.9961	0.0000*	0.0000*	I(1) Stationary
Pesaran-CIPS	**Constant**	**Constant+trend**	**Constant**	**Constant+trend**	**Conclusion**
$LFDI_t$	-3.788*	-3.734*	_	_	I(0) Stationary
$LCOM_t$	-1.728	-1.728	-4.677*	-5.510*	I(1) Stationary

ENG_t	-2.414	-2.496	-6.190*	-6.420*	I(1) Stationary
$LTRA_t$	-1.889	-3.553*	-6.190*	_	I(1) Stationary

Source: Authors estimations using Eviews 13

Note: (*), (**), (***) respectively represents significance at 1%, 5% and 10%.

The stationarity analysis in Table 4 examines key variables, including the log of foreign direct investment (LFDI), communication infrastructure (LCOM), energy infrastructure (ENG), and transport infrastructure (LTRA), using various panel unit root tests. LFDI is non-stationary at levels but becomes stationary after first differencing, indicating it is integrated of order one, I(1). LCOM is stationary at levels with an intercept but non- stationary when a trend is included, requiring differencing to achieve stationarity. ENG shows mixed stationarity at levels (stationary with an intercept, non-stationary with a trend) but becomes stationary after differencing, while LTRA is consistently non- stationary at levels across all tests and achieves stationarity only after differencing. The Pesaran-CIPS test, accounting for cross-sectional dependence, reveals that LFDI is stationary at levels, while LCOM and ENG exhibit non-stationarity at levels but become stationary after differencing. These findings highlight the need for differencing to avoid spurious regression results, aligning with existing literature on FDI and infrastructure variables.

4.2.4 Lag length criteria

In this section, we delve into the determination of the optimal lag length for our model, which is crucial for accurate analysis. The criteria used for selecting the lag length are detailed, and the findings from the evaluation process are comprehensively presented in Table 5. This table summarizes the results and guides the subsequent steps in our analysis.

Table 5. Selection of lag length structure

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-821.6626	NA	29.73926	14.74397	14.84106	14.78337
1	-247.7799	1096.526	0.001403	4.781784	5.267230*	4.978745
2	-218.8349	53.23821	0.001114	4.550622	5.424426	4.905152*
3	-199.0454	34.98487	0.001044	4.482954	5.745114	4.995053
4	-180.0601	32.20731*	0.000995*	4.429644*	6.080161	5.099312
5	-165.7121	23.31539	0.001034	4.459145	6.498020	5.286381

Source: Authors estimations using Eviews 13

Note: The lag length order that each criterion determined to be optimal is indicated by an asterisk (*).

The lag length criteria in Table 5 above help determine the optimal lag length for the model, which is crucial for ensuring robust and accurate results. The table presents various criteria, including the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), each of which identifies the most suitable lag length. The optimal lag length is indicated by asterisks, with the LR, FPE, and AIC criteria suggesting a lag length of 4, while the SC and HQ criteria recommend lag lengths of 1 and 2, respectively. Based on these results, lag length 4 is most frequently identified as optimal, guiding the selection for further analysis. This approach is consistent with standard econometric practices for model specification and lag selection (Lütkepohl, 2005).

4.5 Panel Cointegration Analysis

This section examines the long-term relationship between the model variables using panel cointegration techniques. These tests include the Pedroni Panel Cointegration Test, Kao Panel Cointegration Test, and Johansen-Fisher Panel Cointegration Test, which assess whether the variables share a common trend over time.

4.5.1 Pedroni Panel Cointegration Test results

The Pedroni Panel Cointegration Test is a critical method used to assess the long- term equilibrium relationship between foreign direct investment, communication infrastructure, energy infrastructure and transport infrastructure in a panel data setting. This test provides both panel-specific and group-specific statistics, allowing for a comprehensive evaluation of cointegration across the entire panel as well as within individual groups. With the null hypothesis of no-cointegration among variables and the rejection of this null hypothesis will imply the presence of cointegration among variables.

Table 6. Pedroni panel cointegration test summary results

Panel	***Statistics***	***Probability***	***Weighted statistics***	***Probability***
"-Panel v-Statistics"	-1.143446	0.8736	-1.477930	0.9303
"-Panel rho statistics"	-0.793694	0.2137	-2.382324	0.0086
"-Panel PP-statistics"	-2.633896	0.0042	-4.421668	0.0000
"-Panel ADF-statistics"	-2.875903	0.0020	-4.490136	0.0000
Group				
"-Group rho-Statistics"	-0.749096	0.2269	_	_
"-Group PP-Statistics"	-3.544027	0.0002	_	_
"-Group ADF-Statistics"	-3.379874	0.0004	_	_

In this study focusing on results represented in the above Table 6, the tests findings reveal mixed evidence regarding cointegration among variables in the SADC region. Specifically, most of the estimated probabilities fall below the 5% significance level, leading to the rejection of the null hypothesis of no cointegration. This suggests a long-term relationship exists among the variables studied, aligning with similar findings from research on transport infrastructure dynamics in the ASEAN region by Jones et al. (2022). Seven out of eleven probability values were significant, further supporting the presence of cointegration in the SADC model.

Nonetheless, the results also show variability across different statistics within the Pedroni test. While the Panel v-Statistics failed to reject the null hypothesis, other statistics like the Panel rho-Statistics, Panel PP-Statistics, and Panel ADF-Statistics provided robust evidence of cointegration, particularly at the 1% significance level. The group-specific statistics echoed these mixed outcomes, with some failing to reject the null hypothesis while others confirmed the existence of a cointegrating relationship. These findings underscore the importance of a nuanced interpretation of cointegration results, as the robustness of the Pedroni test across different specifications plays a vital role in understanding complex economic dynamics, as emphasized in studies by Pedroni (1999) and Kao (1999).

4.5.2 Kao Panel Cointegration Test Results

The results from the Kao Panel Cointegration Test presented in Table 7 below indicate a significant long-run relationship between foreign direct investment, Communication infrastructure, energy infrastructure and transport infrastructure under the SADC model in the study.

Table 7. Kao panel cointegration test summary results

Variable	**t-statistics**	**Probability**
ADF	-3.309208	0.0005
Residual variance	0.168361	_
HAC variance	0.080022	_

Source: Authors estimations using Eviews 13

The Kao Panel Cointegration Test results summarised in Table 7, with an ADF t- statistic of -3.309208 and a probability value of 0.0005, provide compelling evidence of a long-term relationship among the variables of the SADC model. The very low p-value signifies that the null hypothesis of no cointegration can be confidently rejected at the 1% significance level, confirming that the variables share a stable equilibrium

relationship over time, these finding are in support of the findings in Table 6 when using the Pedroni panel cointegration test. This implies that despite short-term fluctuations, the variables in the SADC model move together in the long run, which is crucial for the reliability of any subsequent analysis. Such a finding is particularly important in research examining complex interrelationships. The robust cointegration indicated by this low probability value ensures that the long-term dynamics between these variables are consistent, which provides a solid foundation for policy recommendations and theoretical advancements in fields like sustainable development and economic growth (Hashem Pesaran, 2021; Westerlund, 2019).

4.5.3 Johansen-Fisher Panel Cointegration Test Results

The Johansen-Fisher Panel Cointegration Test results, as shown in Table 8 below, provide insights into the existence of cointegration among the variables. This third cointegration test confirms the cointegration results found using Pedroni and Kao cointegration test in Table 6 and 7, respectively.

Table 8. Johansen-Fisher Panel Cointegration test summary results

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob Value	Fisher Stat.* (from max-eigen test)	Prob Value
None	20.76	0.0078*	18.84	0.0158*
At most 1	9.635	0.2916	5.430	0.7108
At most 2	7.852	0.4481	6.958	0.5411
At most 3	7.113	0.5244	7.113	0.5244

Source: Authors estimations using Eviews 13

Note: At 5% significance level, the symbol (*) signifies the null hypothesis rejection of there is no cointegration among variables.

The Fisher statistics derived from both the trace test and the max-eigenvalue test indicate the rejection of the null hypothesis of no cointegration at the 5% significance level for the case of no cointegrating equations at None category. Specifically, the Fisher statistic values of 20.76 (with a p-value of 0.0078) from the trace test and 18.84 (with a p-value of 0.0158) from the max-eigen test both reject the null hypothesis, confirming the presence of at least one cointegrating relationship among the variables in the SADC model. This suggests that the variables are linked over the long term, moving together despite short-term deviations. However, for higher levels of hypothesized cointegrating equations e.g., At most 1, At most 2, and At most 3, the test statistics do not reject the null hypothesis, implying that the data does not support the presence of multiple cointegrating vectors. These findings are crucial as they provide a foundation for understanding the long-run equilibrium relationships within the dataset, which is vital for making informed economic policy decisions or further econometric modelling in the context of the study (Narayan et al., 2021).

4.6 Panel Auto-Regressive Distributed Lag (PARDL) results

The Panel ARDL estimates show the impact of energy infrastructure, communication infrastructure, and transport infrastructure on the foreign direct investment in both the short and long terms. Additionally, the results encompass ECM estimates for SADC model, showing the speed at which the model moves towards equilibrium from the short to long run.

Table 9. Results of the panel ARDL summarized both long run and short run

Variable	Long run Coefficients	Probability (L)	Short run Coefficients	Probability (S)
ENG	0.089853	0.0001	-0.001344	0.9382
LCOM	-0.372102	0.2965	0.580264	0.0893
LTRA	0.557887	0.0449	0.289253	0.4964
ECM	-0.437061			0.0442

Constant (β_0)	0.173144			0.7129

Source: Authors estimations using Eviews 13

$$LFDI_{it} = 0.1731 + 0.0898 * ENG_{it} - 0.3721 * LCOM_{it} + 0.5578 * LTRA_{it} + \varepsilon_{it} \ldots\ldots\ldots(1)$$

Based on the results from the Panel Auto-Regressive Distributed Lag (PARDL) model in Table 9 above, the impact of several types of infrastructure on foreign direct investment (FDI) is evaluated both in the short and long term.

The regression model represented by equation (1) above extracted from the long run coefficient results, expresses the relationship between Foreign Direct Investment (LFDI) and three key infrastructure variables: energy (ENG), communication (LCOM), and transport (LTRA). The model shows that energy infrastructure has a positive impact on FDI, while communication infrastructure has a negative effect, and transport infrastructure positively influences FDI. The constant term reflects the base level of FDI when all other factors are zero.

In the long run, the estimated coefficients indicate that energy infrastructure has a positive effect on FDI, with a coefficient of 0.089853 and a highly significant probability value of 0.0001. This suggests that a 10% improvement in energy infrastructure is likely to increase FDI by approximately 0.898% in the long term. On the other hand, communication infrastructure has a negative coefficient of -0.372102, though it is not statistically significant at probability value of 0.2965. This implies that a 10% improvement in communication infrastructure could potentially reduce FDI by about 3.721%, although this effect is not statistically significant and therefore may not hold. Transport infrastructure, however, shows a positive and significant impact with a coefficient of 0.557887 and associated probability value of 0.0449, suggesting that a 10% enhancement in transport infrastructure is associated with a 5.579% increase in FDI over the long term. This is supported by evidence that transport infrastructure significantly influences FDI decisions (Osei-Assibey & Agyemang, 2021).

In the short run, the coefficients show different dynamics. Energy infrastructure (ENG) has a very small negative coefficient of -0.001344, which is not statistically significant because of the probability value of 0.9382, indicating that short-term changes in energy infrastructure have minimal impact on FDI. Communication infrastructure (LCOM) shows a positive coefficient of 0.580264, although it is marginally significant at 10% level with a probability value of 0.0893. This could suggest that while communication infrastructure has some positive effect on FDI in the short run, it is not robust enough to be deemed significant. Transport infrastructure (LTRA) has coefficient of 0.289253 with a probability value of 0.4964, indicating that its short-term impact on FDI is not statistically significant. This suggests that while transport infrastructure is crucial, its short-term effects may be less pronounced (Sharma & Khera, 2023).

The Error Correction Model coefficient of -0.437061 with a significant probability value of 0.0442 indicates that the model adjusts to equilibrium at a rate of approximately 43.7% per period. A negative error correction term is rectified within a single period. Both the long-run and short-run deviations are elucidated by the error correction term, consistent with findings by Menegaki (2019) and Letsoalo (2021). This high rate suggests that any deviation from the long-run equilibrium is corrected quickly. This finding is consistent with literature on the speed of adjustment in ECM models (Zhou & Wang, 2022).

The long-run elasticity coefficients suggest that energy and transport infrastructures are crucial for attracting FDI, while communication infrastructures impact is less clear. In contrast, short-term effects are less pronounced, especially for energy and transport infrastructures.

4.7 Panel correlated standard error (PCSE) results

Following the methodology in Section 3, Table 10 provides the results of the Panel Correlated Standard Error (PCSE) method, which also accounts for cross-sectional dependence in the panel data. This method offers robust standard errors to address potential biases and enhance the reliability of the models estimates.

Table 10. Findings from the Panel Correlated Standard Error (PCSE) Method for Panel Data Modelling

MODELS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	LFDI	LFDI	LFDI	LFDI	LFDI	LFDI	LFDI	LFDI	LFDI
ENG	0.00184	0.00223	0.00332	0.00184*	0.00223	0.00332	0.00184	0.00223	0.00332
	(1.577)	(1.155)	(1.297)	(1.829)	(1.378)	(1.633)	(1.573)	(1.126)	(1.434)
LCOM	0.822***	0.634***	0.593***	0.822***	0.634***	0.593***	0.822***	0.634***	0.593***
	(8.975)	(5.728)	(5.600)	(11.99)	(7.277)	(6.726)	(12.71)	(7.129)	(7.127)
LTRA	0.208**	0.327**	0.366***	0.208**	0.327**	0.366***	0.208**	0.327***	0.366***
	(2.003)	(2.156)	(3.039)	(2.430)	(2.311)	(3.272)	(2.537)	(2.615)	(3.421)
Constant	0.901**	1.563**	1.538***	0.901**	1.563**	1.538***	0.901**	1.563**	1.538***
	(2.041)	(2.015)	(2.801)	(2.159)	(2.006)	(2.796)	(2.128)	(2.311)	(2.978)
Observations	132	132	132	132	132	132	132	132	132
R-squared	0.730	0.668	0.980	0.730	0.668	0.980	0.730	0.668	0.980
Number of countries	4	4	4	4	4	4	4	4	4
chi2 (Wald Statistic)	312.7***	81.09***	183.2***	334.1***	91.78***	166.4***	357.6***	118.7***	214.3***

Authors computations. Z-statistics in parentheses, *** p<0.01, ** p<0.05 and * p<0.1.

The Panel Correlated Standard Error (PCSE) model results presented in Table 10 address the cross-sectional dependence issue often present in panel data as seen in Table 2, thus providing more reliable standard errors and robust results. This model improves the precision of the parameter estimates by accounting for correlations across the countries in your sample. The results show a varied impact of energy, communication, and transport infrastructure on Foreign Direct Investment (FDI), which holds important implications for policymakers focusing on infrastructure development to attract FDI.

Firstly, the coefficient for energy infrastructure (ENG), although positive across all models, is only statistically significant at the 10% level in one model. Specifically, the ENG variable exhibits a weak positive influence on FDI in model 4, with a coefficient of 0.00184 and a p-value slightly below 0.1, indicating marginal significance. In the remaining models, the energy infrastructures impact is not significant, suggesting that its influence on FDI is inconsistent and may depend on additional contextual factors, such as the quality and efficiency of energy supply. This finding aligns with the broader literature, which suggests that while energy infrastructure is crucial for economic development, its direct relationship with FDI may vary across regions and over time, depending on energy reliability and access (Bannister & Sauvant, 2021).

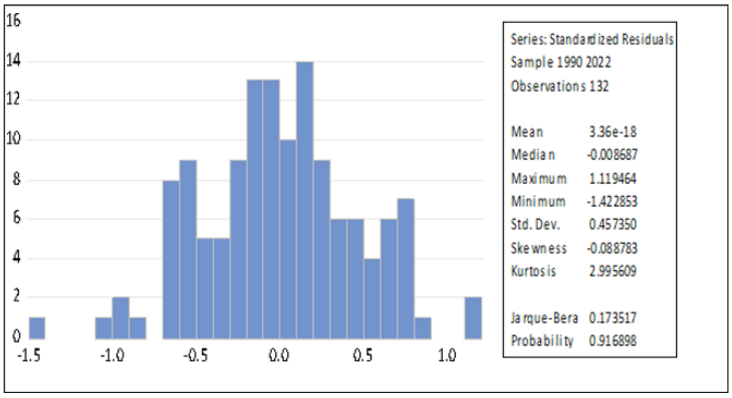
In contrast, communication infrastructure (LCOM) consistently shows a highly significant positive relationship with FDI across all models, with coefficients ranging from 0.593 to 0.822. The statistical significance at the 1% level highlights that communication infrastructure is a critical determinant of FDI inflows. The strong and consistent effect of LCOM underscores the role of modern communication systems in facilitating international business operations, which is consistent with findings from recent empirical studies on FDI determinants in developing countries (Asiedu, 2020). Improved communication networks reduce transaction costs and enhance the efficiency of business processes, making countries more attractive to foreign investors.

The results for transport infrastructure (LTRA) reveal a positive and statistically significant relationship with FDI, with significance at the 5% level in earlier models and increasing to the 1% level in later models. The coefficients, ranging between 0.208 and 0.366, suggest that improvements in transport infrastructure significantly contribute to FDI inflows. This finding is consistent with previous studies indicating that reliable and efficient transportation systems reduce the costs of moving goods and services, making a country more competitive in attracting investment (Fedderke & Bogetic, 2022). The significance of transport infrastructure, particularly in developing countries, is critical, as it enhances access to markets and facilitates trade.

Overall, the findings emphasize that communication and transport infrastructure are key factors in attracting FDI, while the effect of energy infrastructure is less robust in this context. This suggests that policymakers in the sample countries should prioritize investments in communication and transport infrastructure to effectively boost FDI. The high R-squared values, especially in later models, indicate a strong explanatory power, meaning the model explains a sizeable portion of the variance in FDI inflows. These results contribute to the growing evidence that infrastructure development is vital for fostering economic growth and attracting foreign investment (Goswami et al., 2023).

4.8 Diagnostic testing results

This section presents the results of diagnostic tests to assess the validity of the model. Diagnostic tests are essential to ensure that the model conforms to the assumptions required for reliable regression analysis. In this study, heteroscedasticity and autocorrelation issues were managed by employing the Panel Correlated Standard Error (PCSE) model in Table 10 above, which corrects for cross-sectional dependence and ensures robust standard errors (Beck & Katz, 1995). The Jarque-Bera test was used to assess whether the residuals of the model are normally distributed. This test evaluates the joint hypothesis of skewness and kurtosis, ensuring that the error terms follow a normal distribution, which enhances the reliability of the statistical results (Gujarati & Porter, 2009). Below are the results for the normality test.



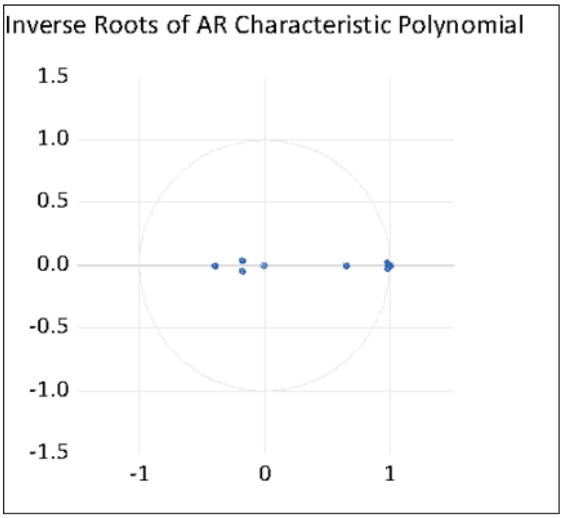
Source: Authors estimations using EViews 13

FIGURE 1
NORMALITY TEST RESULTS

From the above results in Figure 1 the bell-shaped graph, combined with a Kurtosis value of 2.995609 and a Jarque-Bera probability of 0.916898, suggests that the data distribution is normal. A Kurtosis value close to 3 indicates that the data has a shape like a normal distribution, with moderate tails and a peak consistent with the Gaussian bell curve. The high Jarque-Bera probability (greater than 0.05) further supports the null hypothesis of normality, implying that there is no significant deviation from a normal distribution. Similar findings were reported by Hansen and Lunde (2005), who observed comparable kurtosis values and non-significant Jarque-Bera test results in their analysis of financial time series, suggesting that the data adhered closely to normality.

4.9 Stability Testing

The stability of the model is assessed using the inverse roots of the autoregressive (AR) characteristic polynomial. According to Hamilton (1994) and Greene (2008), this test ensures that all roots lie within the unit circle, indicating that the model is stable. Figure 2 presents the results of this analysis, providing a visual representation of the model's stability.



Source: Authors estimations using EViews 13

FIGURE 2
INVERSE ROOTS OF AR CHARACTERISTIC POLYNOMIAL RESULTS

The study also employs the Inverse Root of AR Characteristics test to assess the stability of the model. This test ensures that the estimated coefficients result in a stable system over time. In Figure 2, all AR roots fall within the unit circle, indicating that the model is stable. According to Wooldridge (2019), when the AR roots lie within the unit circle, it suggests that the model does not exhibit explosive behaviour, ensuring that shocks to the system dissipate over time rather than leading to erratic or unstable outcomes. This stability is critical for ensuring the reliability and accuracy of the models results, allowing for meaningful policy implications and long-term predictions.

4.10 Dumitrescu Hurlin Panel Causality Test

The results and interpretations of the Granger causality tests for the SADC region are shown in this section using the Dumitrescu Hurlin Panel Causality test are presented in Table 11 below.

Table 11. Dumitrescu Hurlin Panel Causality test summary results

Null Hypothesis:	W-Stat.	Zbar-Stat.	P-value	Decision
LCOM ➔ LFDI	6.11064	3.34886	0.0008	Reject Null
LFDI ➔ LCOM	1.25030	-0.77809	0.4365	Accept Null
ENG ➔ LFDI	4.89247	2.31450	0.0206	Reject Null
LFDI ➔ ENG	2.59622	0.36474	0.7153	Accept Null
LTRA ➔ LFDI	1.81803	-0.29603	0.7672	Accept Null
LFDI ➔ LTRA	1.28909	-0.74515	0.4562	Accept Null
ENG ➔ LCOM	2.99314	0.70177	0.4828	Accept Null
LCOM ➔ ENG	6.29390	3.50446	0.0005	Reject Null
LTRA ➔ LCOM	1.14717	-0.86566	0.3867	Accept Null
LCOM ➔ LTRA	4.63484	2.09574	0.0361	Reject Null
LTRA ➔ ENG	1.31041	-0.72705	0.4672	Accept Null
ENG ➔ LTRA	5.68986	2.99157	0.0028	Reject Null

Note: (➔) denotes the null hypothesis that there is no Granger causality.

The results of the Dumitrescu Hurlin Panel Causality Test presented in Table 11 provide insights into the directional relationships between the variables in the study. The findings reveal significant causal relationships in several instances, particularly between communication infrastructure (LCOM) and foreign direct investment (LFDI), energy infrastructure (ENG) and LFDI, and various interactions between LCOM, ENG, and transport infrastructure (LTRA). Specifically, the test results indicate that LCOM Granger-causes LFDI, as evidenced by a W-statistic of 6.11064 and a p-value of 0.0008 at 1% level of significance, leading to the rejection of the null hypothesis of no causality. Conversely, LFDI does not Granger-cause LCOM, as indicated by the acceptance of the null hypothesis with p-value of 0.4365. This suggests that improvements in communication infrastructure lead to increased foreign direct investment, but the reverse is not true.

Similarly, ENG is found to Granger-cause LFDI with a W-statistic of 4.89247 and a p- value of 0.0206, supporting the hypothesis that energy infrastructure development drives foreign direct investment at 5% level. However, LFDI does not appear to influence ENG at 5% level, having a p-value of 0.7153. The analysis also uncovers unidirectional causality between LCOM and ENG, where LCOM Granger-causes ENG at 1% level, with p-value of 0.0005. Additionally, there is evidence of unidirectional causality from LCOM to LTRA at 5% level with a p-value of 0.0361 and from ENG to LTRA at 1% level having a p-value of 0.0028, indicating that improvements in communication and energy infrastructure can lead to better transport infrastructure, but not the other way around. These findings are significant as they highlight the importance of infrastructure development in driving foreign direct investment and underscore the interconnected nature of different infrastructure components within the economic framework, Narayan and Smyth found the similar causality results using the D-H panel granger causality tests (Narayan & Smyth, 2016).

5. CONCLUSION AND RECOMMENDATIONS

The study effectively demonstrated the significant impact of infrastructure investments specifically in energy, transport, and communication on Foreign Direct Investment (FDI) inflows in selected SADC countries. Energy infrastructure emerged as a critical factor, positively and significantly influencing FDI due to its importance in ensuring reliable and consistent power for foreign investors. Transport infrastructure also showed a positive and meaningful relationship, highlighting its role in reducing logistical costs and enhancing investment attractiveness. However, the study found a negative and statistically insignificant relationship

between communication infrastructure and FDI, underscoring the need for further investment in digital communication technologies to remain competitive in a rapidly digitizing global economy. The bidirectional causal relationship between energy and communication infrastructure investments suggests a reinforcing cycle that can further amplify economic benefits if well-coordinated. Policymakers are advised to adopt an integrated approach to infrastructure development, focusing on energy, transport, and digital communication to maximize the overall impact on FDI inflows and regional economic growth.

To enhance FDI attraction, SADC countries should prioritize stable and forward- looking policies, particularly in infrastructure investment. Policymakers are encouraged to explore public-private partnerships for energy sector reforms, focusing on both traditional and renewable energy sources. Investment in digital communication networks, such as broadband infrastructure, is essential for attracting technology- driven industries and supporting local businesses. Additionally, improving transport infrastructure through better roads, railways, and ports will reduce logistical barriers and further enhance investment appeal. Institutional capacity building and regional collaboration, especially for cross-border infrastructure projects, are critical to ensure sustainable development. Long-term financing from international organizations like the World Bank and African Development Bank (AfDB) can support large-scale projects. Despite its contributions, the study acknowledges limitations, including its focus on a subset of SADC countries and reliance on secondary data, which may limit generalizability. Future research could address these limitations by expanding geographic scope and incorporating additional variables to deepen understanding.

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